



# Joint Posterior Revision of NLP Annotations via Ontological Knowledge

Marco Rospocher

Francesco Corcoglioniti



**IJCAI - ECAI 2018**

**July 13-19, 2018  
Stockholm  
Sweden**

# Context: Knowledge Extraction

Kia has hired Peter Schreyer as chief design officer.

# Context: Knowledge Extraction

Kia has hired Peter Schreyer as chief design officer.

# Context: Knowledge Extraction

Organization

Kia has hired Peter Schreyer as chief design officer.

NLP Tasks:

- Named Entity Recognition and Classification (NERC)

# Context: Knowledge Extraction

Organization

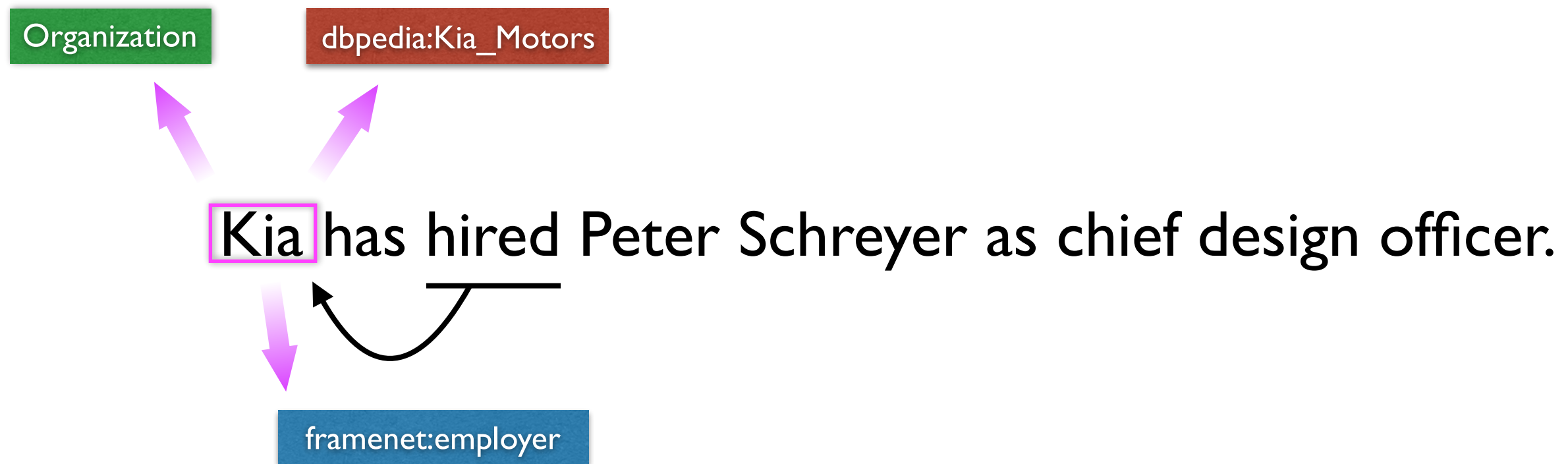
dbpedia:Kia\_Motors

**Kia** has hired Peter Schreyer as chief design officer.

NLP Tasks:

- Named Entity Recognition and Classification (NERC)
- Entity Linking (EL)

# Context: Knowledge Extraction



## NLP Tasks:

- Named Entity Recognition and Classification (NERC)
- Entity Linking (EL)
- Semantic Role Labeling (SRL)

...

# Motivating Examples

Mr. **Washington** was runner-up at Wimbledon in 1996.

# Motivating Examples


Mr. **Washington** was runner-up at Wimbledon in 1996.

## Stanford CoreNLP

<http://nlp.stanford.edu:8080/corenlp>

1	Mr. <b>Washington</b> was runner-up at Wimbledon in 1996.
---	---

**Person** **Location** **Date**





# Motivating Examples


Mr. **Washington** was runner-up at Wimbledon in 1996.

## Stanford CoreNLP

<http://nlp.stanford.edu:8080/corenlp>

1	Mr. <b>Washington</b> was runner-up at Wimbledon in 1996.
---	---

Person Location Date



<http://demo.dbpedia-spotlight.org>

Mr. Washington was runner-up at Wimbledon in 1996.

[http://dbpedia.org/resource/Washington\\_\(state\)](http://dbpedia.org/resource/Washington_(state))




# Motivating Examples

Mr. **Washington** was runner-up at Wimbledon in 1996.

## Stanford CoreNLP

<http://nlp.stanford.edu:8080/corenlp>

	<b>Person</b>		<b>Location</b>		<b>Date</b>
1	Mr. Washington	was runner-up at	Wimbledon	in	1996.



<http://demo.dbpedia-spotlight.org>

Mr. Washington was runner-up at Wimbledon in 1996.

[http://dbpedia.org/resource/Washington\\_\(state\)](http://dbpedia.org/resource/Washington_(state))



The **GW Bridge** is a double-decked suspension bridge over the Hudson.

# Motivating Examples

Mr. **Washington** was runner-up at Wimbledon in 1996.

## Stanford CoreNLP

<http://nlp.stanford.edu:8080/corenlp>

1 Mr. **Washington** was runner-up at Wimbledon in 1996.

Person Location Date



<http://demo.dbpedia-spotlight.org>

Mr. **Washington** was runner-up at Wimbledon in 1996.

[http://dbpedia.org/resource/Washington\\_\(state\)](http://dbpedia.org/resource/Washington_(state))



The **GW Bridge** is a double-decked suspension bridge over the Hudson.



<http://demo.dbpedia-spotlight.org>

The **GW Bridge** is a double-decked **suspension bridge** over the Hudson.

[http://dbpedia.org/resource/George\\_Washington\\_Bridge](http://dbpedia.org/resource/George_Washington_Bridge)



# Motivating Examples

Mr. **Washington** was runner-up at Wimbledon in 1996.

## Stanford CoreNLP

<http://nlp.stanford.edu:8080/corenlp>

1 Mr. **Washington** was runner-up at Wimbledon in 1996.

Person Location Date



<http://demo.dbpedia-spotlight.org>

Mr. **Washington** was runner-up at Wimbledon in 1996.

[http://dbpedia.org/resource/Washington\\_\(state\)](http://dbpedia.org/resource/Washington_(state))



The **GW Bridge** is a double-decked suspension bridge over the Hudson.

## Stanford CoreNLP

<http://nlp.stanford.edu:8080/corenlp>

1 The **GW Bridge** is a double-decked suspension bridge over the Hudson.

Org



<http://demo.dbpedia-spotlight.org>

The **GW Bridge** is a double-decked suspension bridge over the Hudson.

[http://dbpedia.org/resource/George\\_Washington\\_Bridge](http://dbpedia.org/resource/George_Washington_Bridge)



# Abstracting

... token<sub>1</sub> token<sub>2</sub> token<sub>3</sub> token<sub>4</sub> token<sub>5</sub> token<sub>6</sub> ....

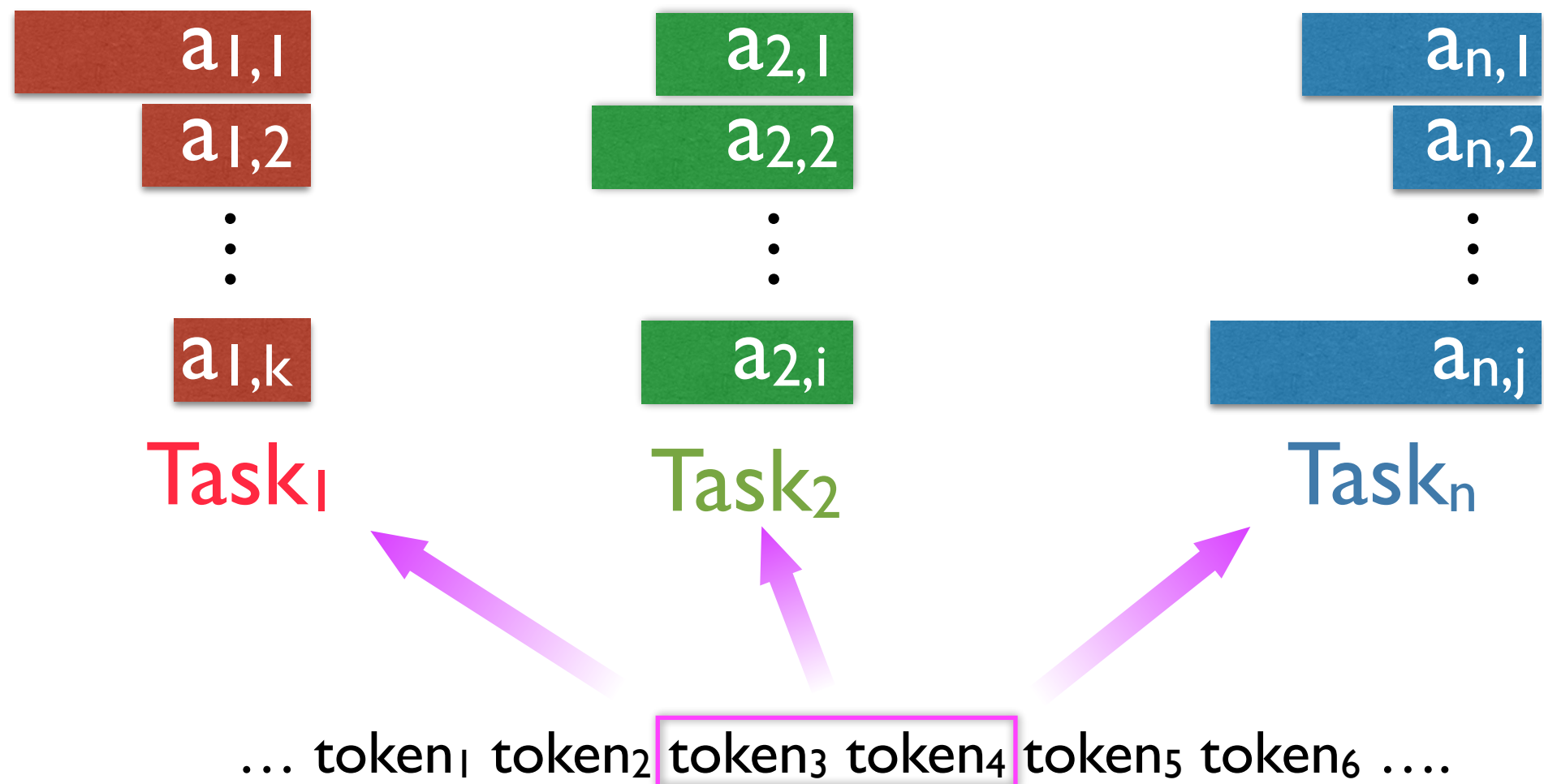
# Abstracting

... token<sub>1</sub> token<sub>2</sub> token<sub>3</sub> token<sub>4</sub> token<sub>5</sub> token<sub>6</sub> ....

# Abstracting

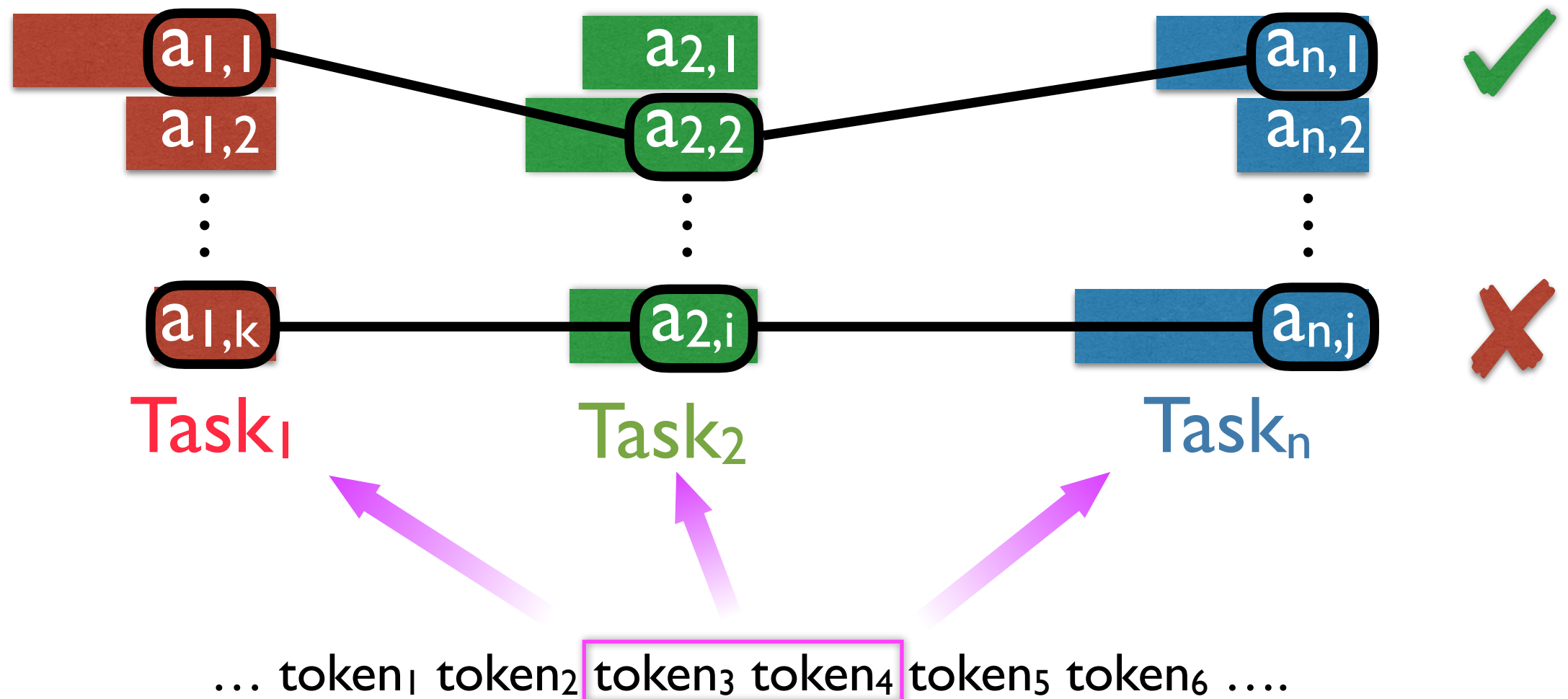


# Abstracting

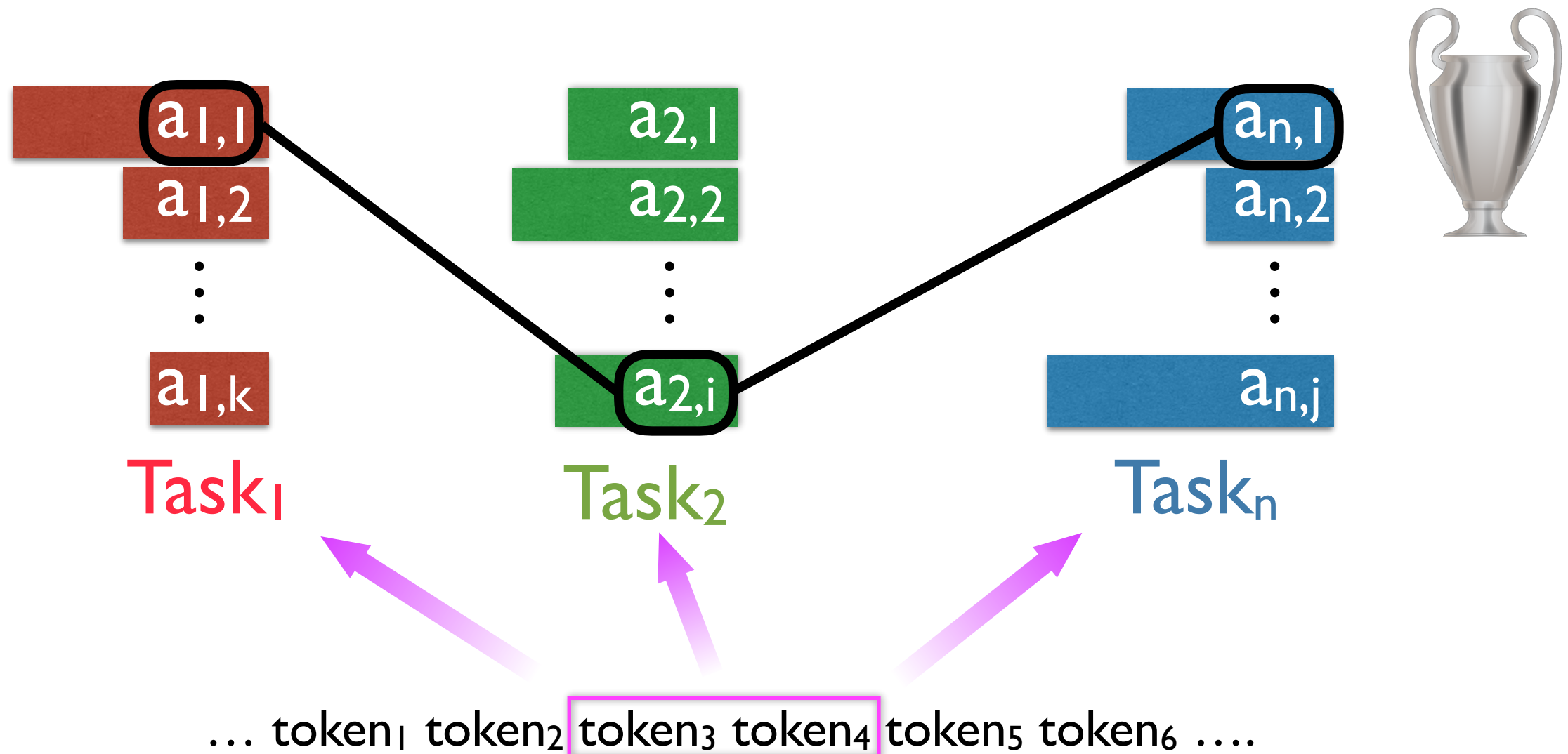




# Abstracting



# Abstracting

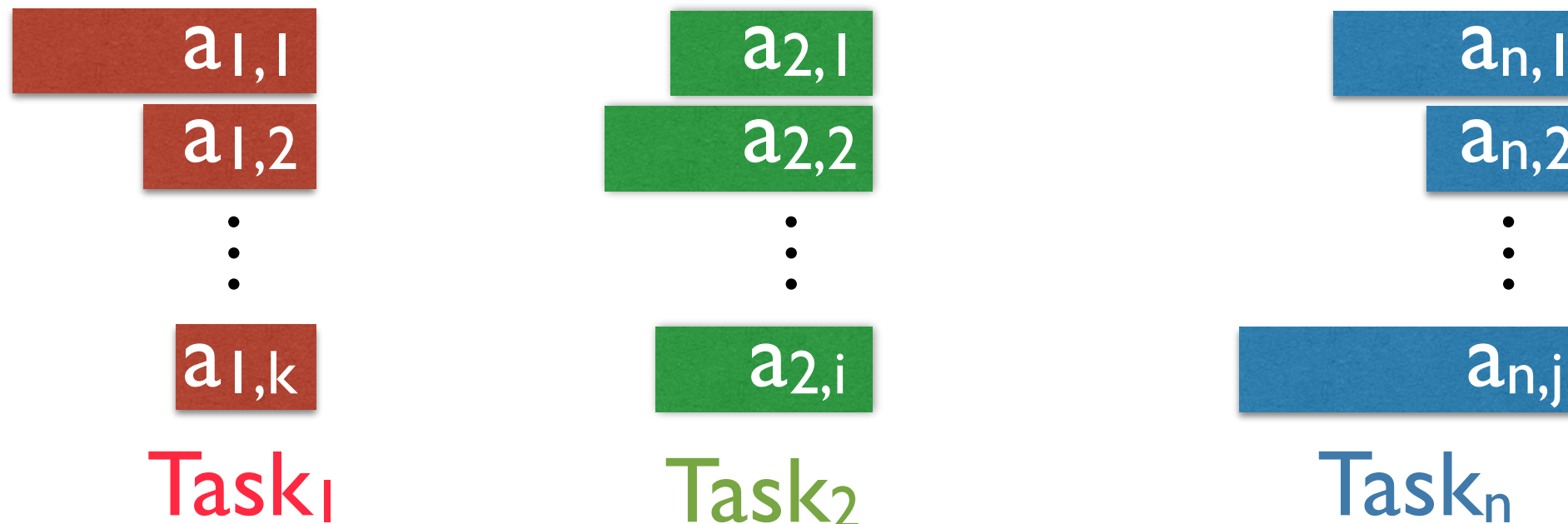
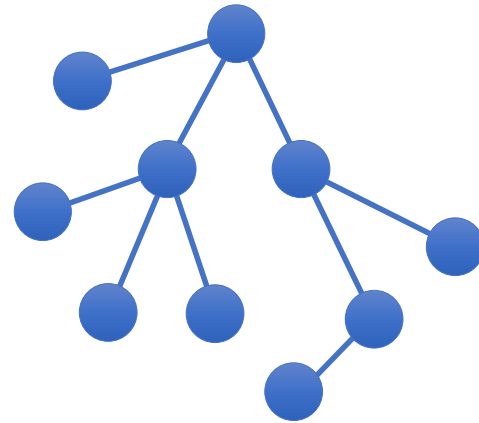


# RESEARCH PROBLEM

How can we assess and improve the coherence of the various NLP annotations on an entity mention?

# In a nutshell

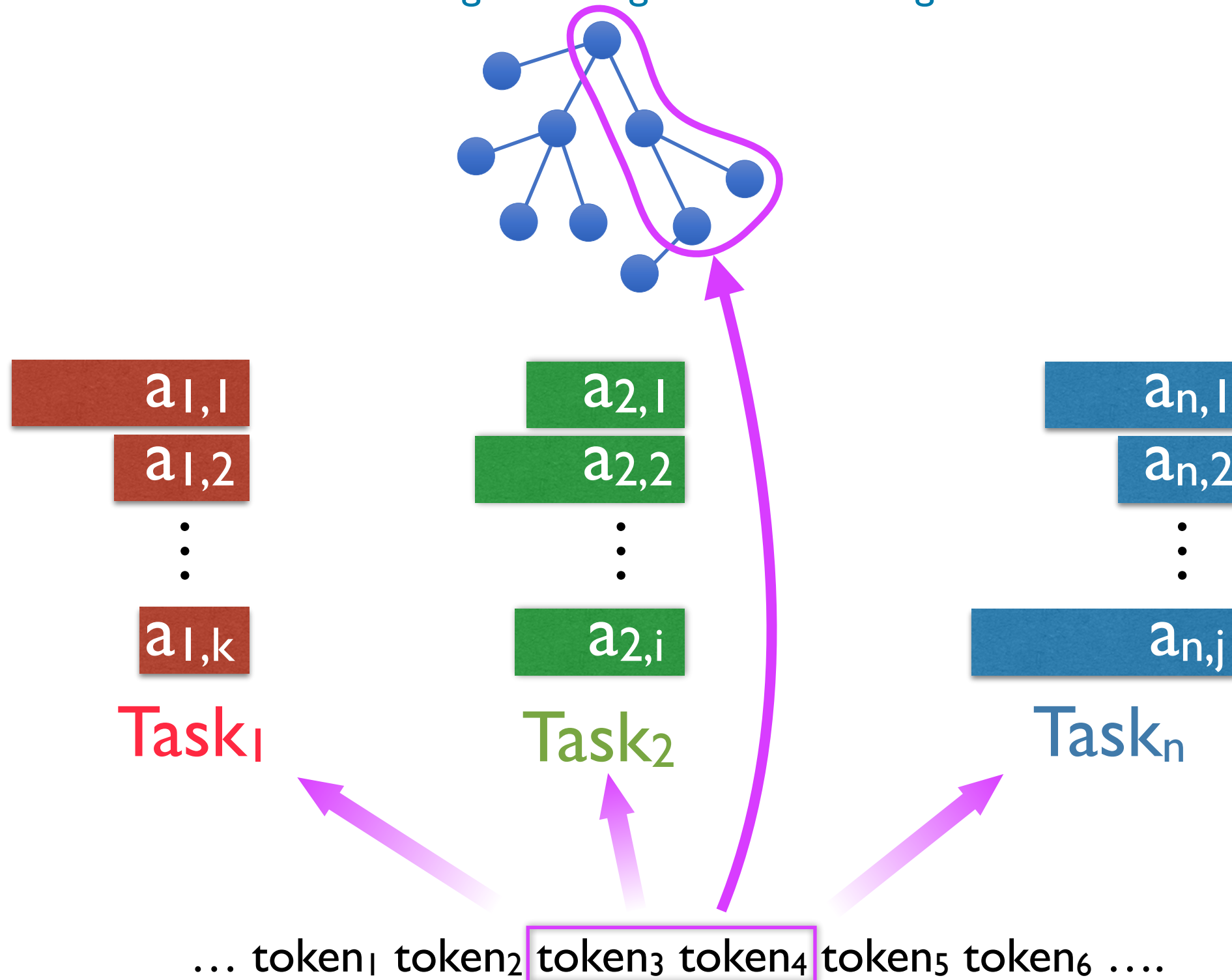
ontological background knowledge



... token<sub>1</sub> token<sub>2</sub> token<sub>3</sub> token<sub>4</sub> token<sub>5</sub> token<sub>6</sub> ....

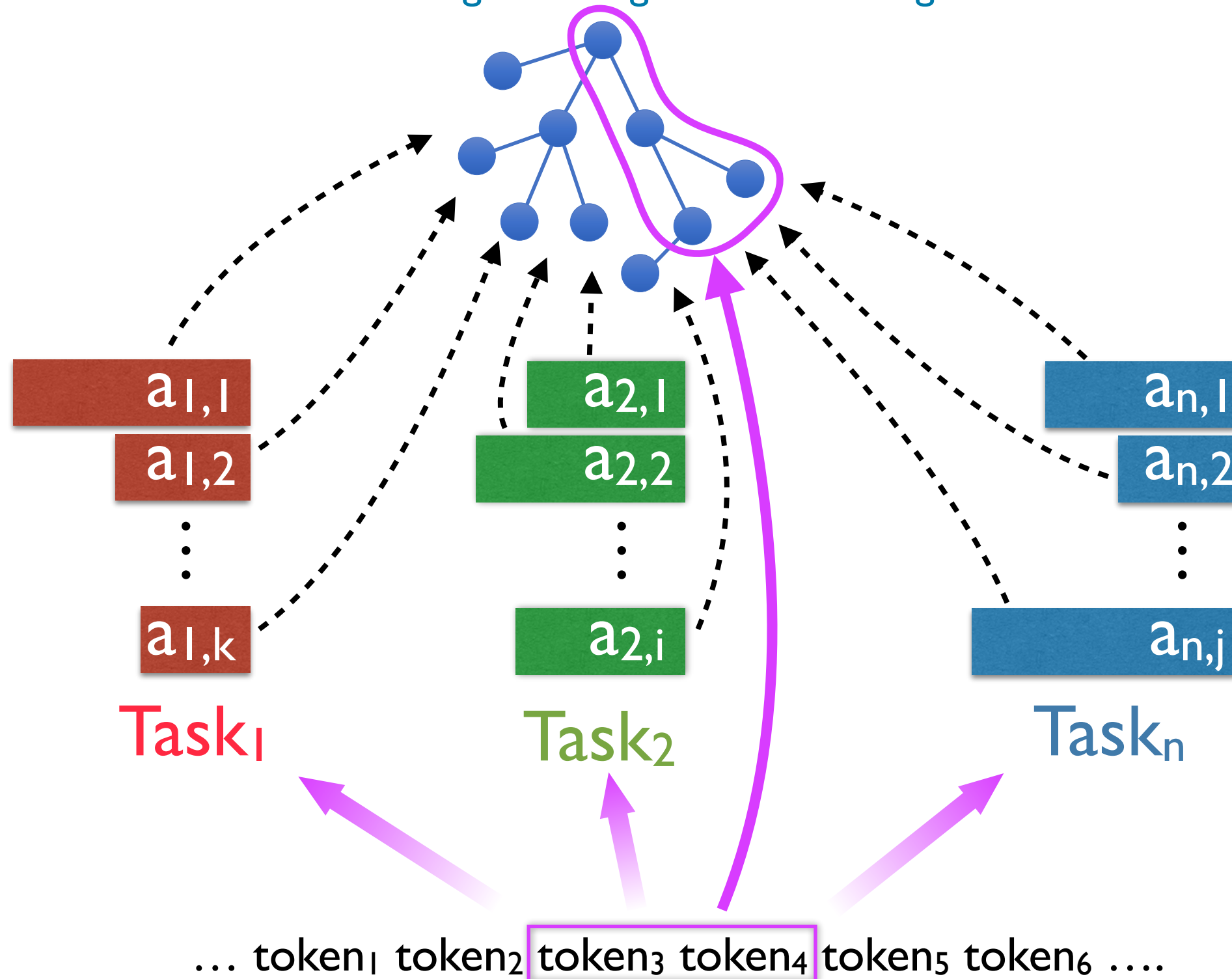
# In a nutshell

ontological background knowledge



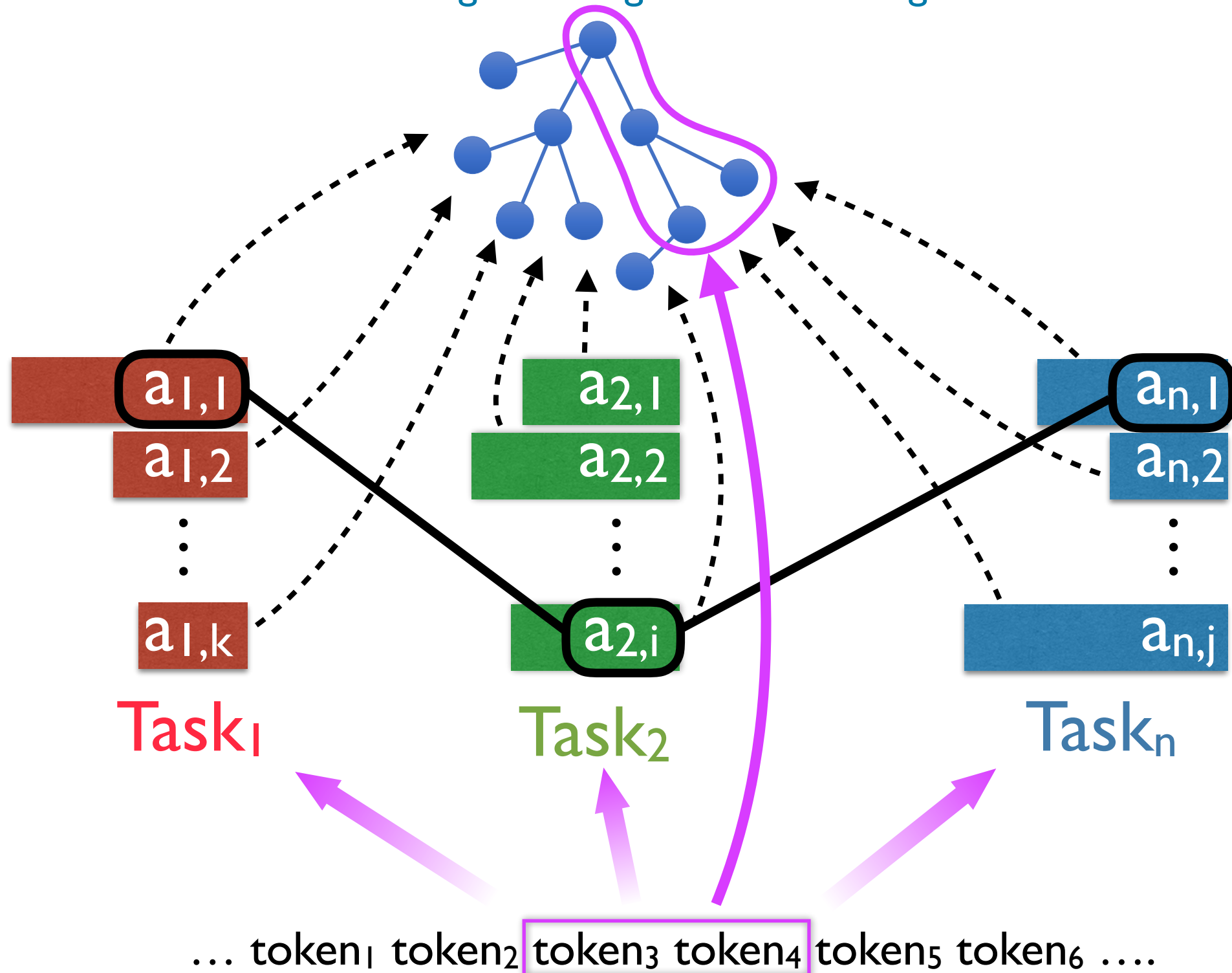
# In a nutshell

ontological background knowledge



# In a nutshell

ontological background knowledge



# Contributions

1. **JPARK**: a probabilistic model capable to estimate a posteriori the overall confidence of NLP annotations
2. A concrete instantiation of the model for NERC and EL (using YAGO as ontological knowledge)
3. Application of the NERC and EL model to revise the annotations of Stanford NER and DBpedia Spotlight





JPARK

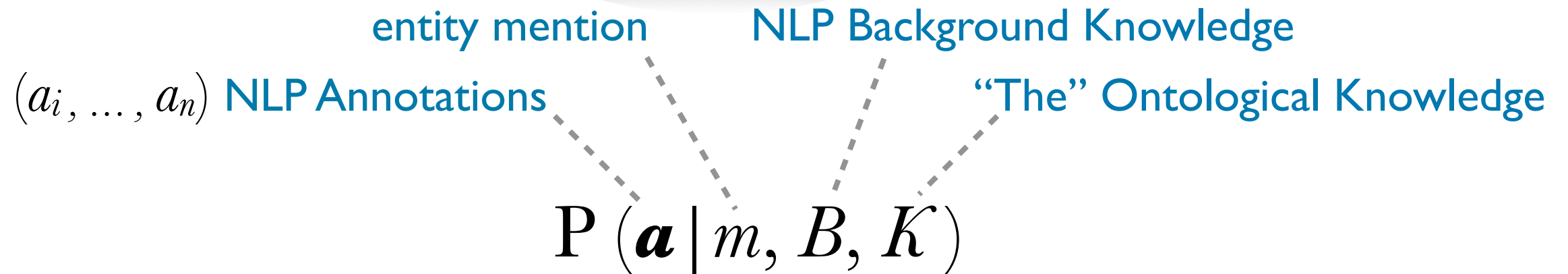


# The JPARK Model

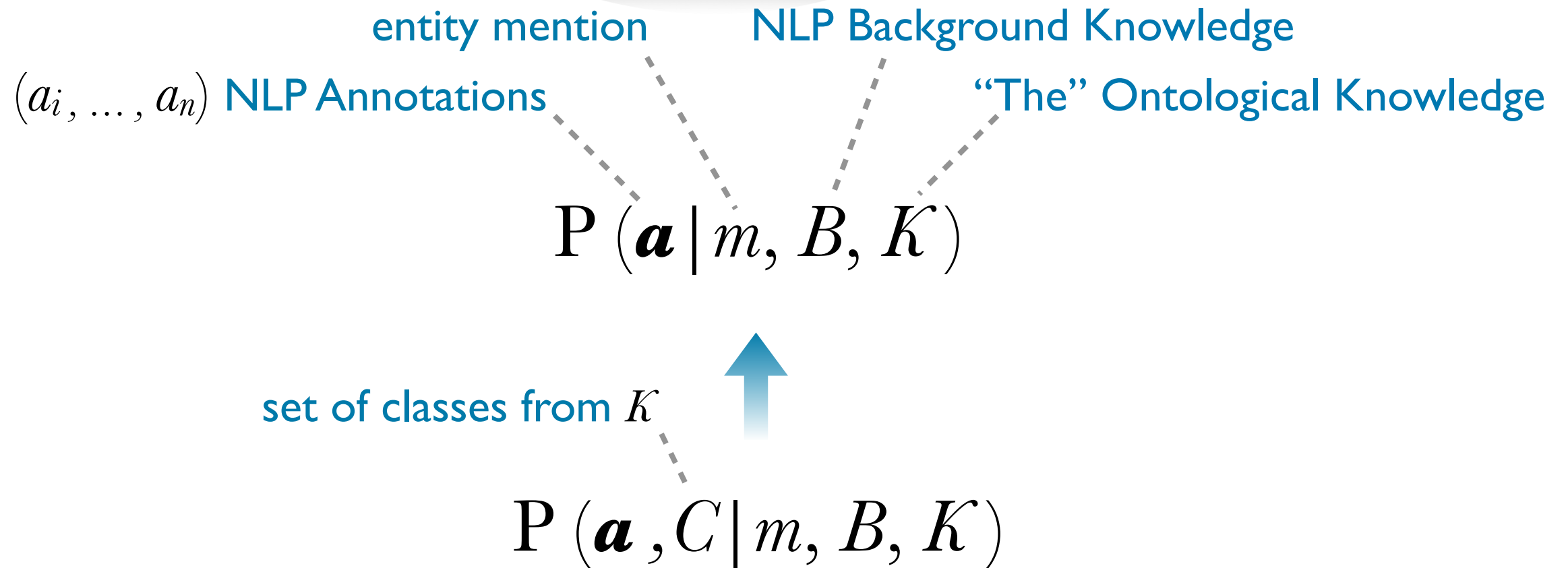
The JPARK logo graphic consists of a thick black curved line above a thinner, lighter grey curved line, both centered under the word 'JPARK' in the title.

$$P(\mathbf{a} | m, B, K)$$

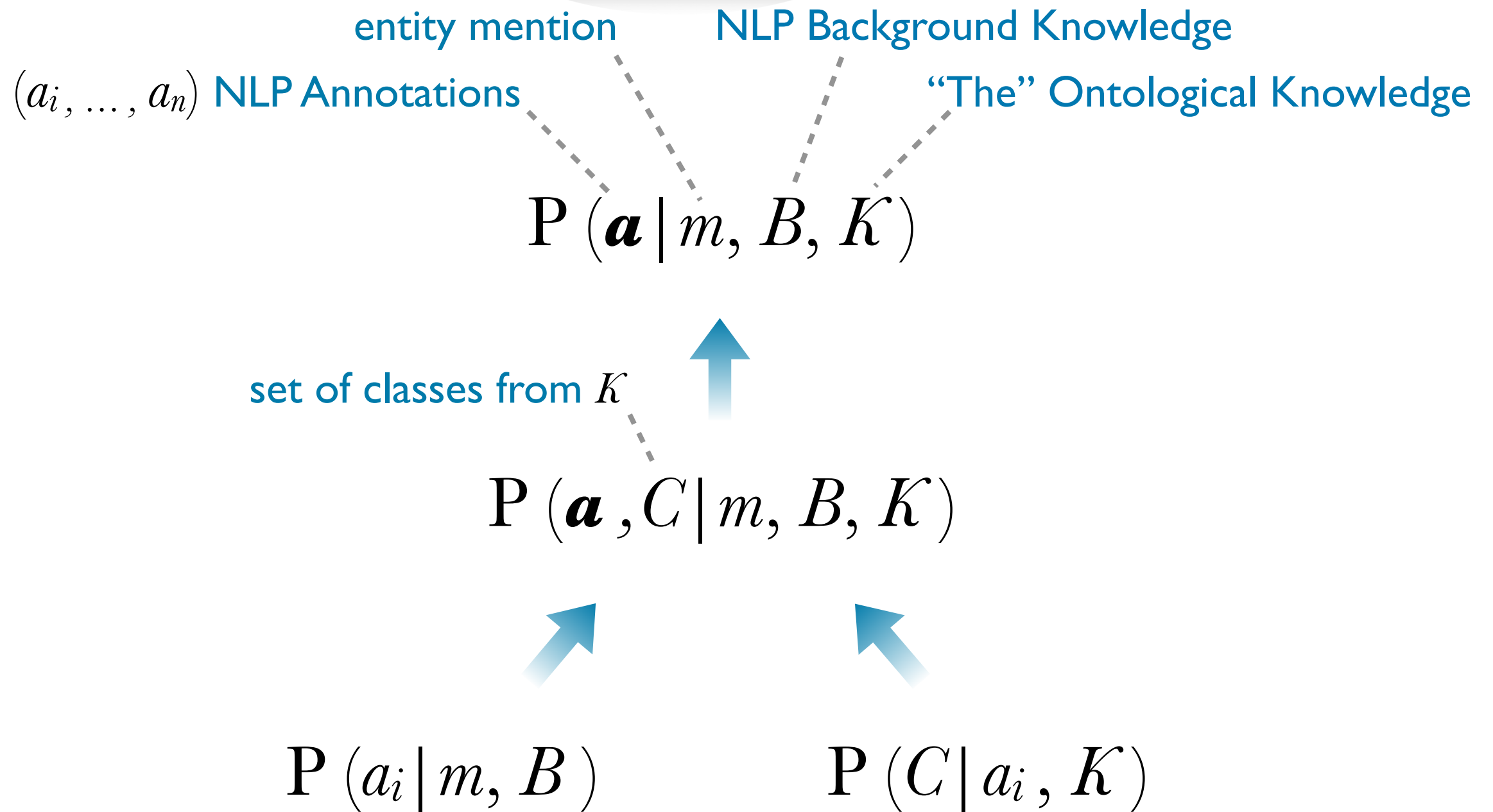
# The JPARK Model



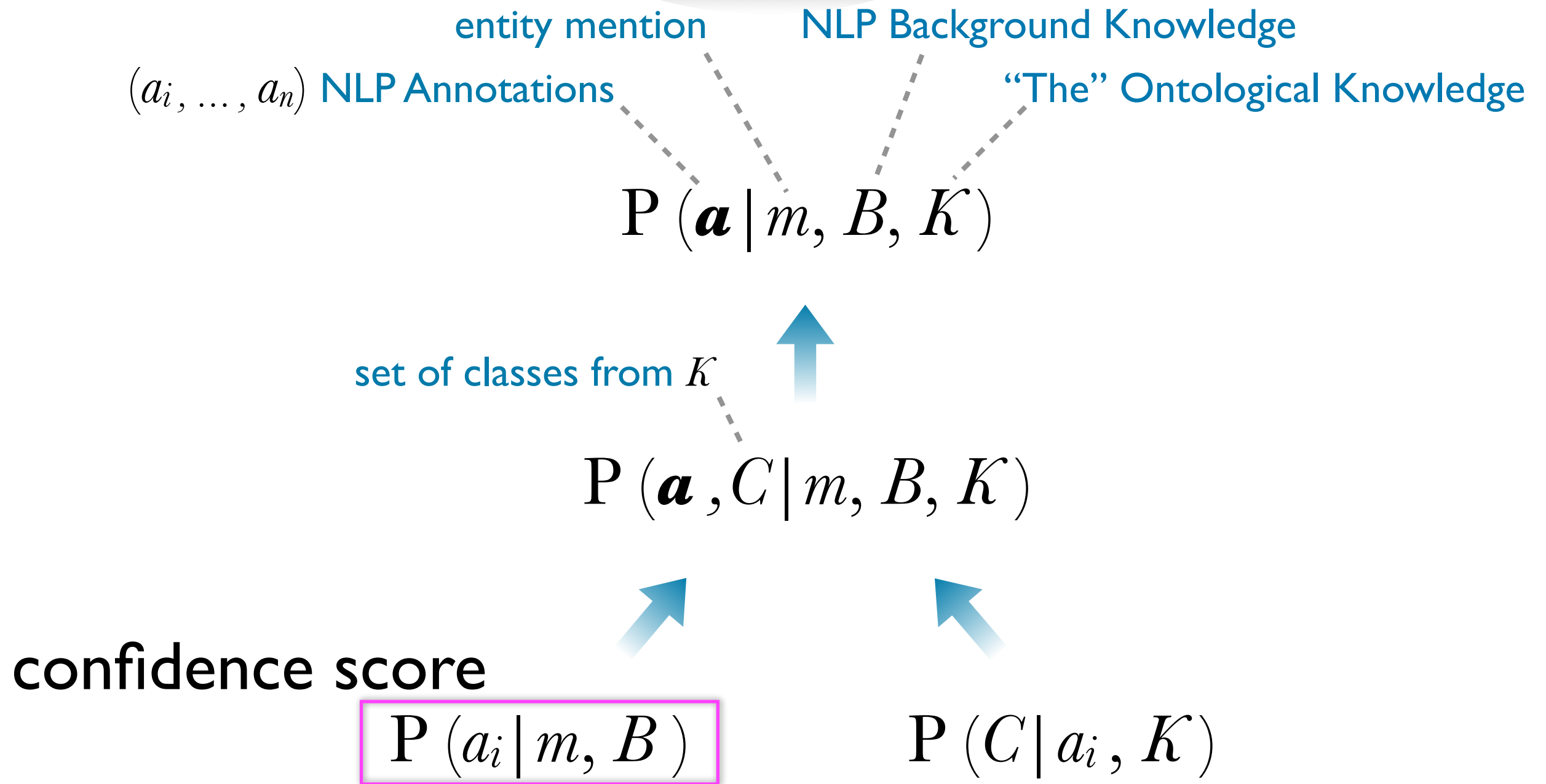
# The JPARK Model



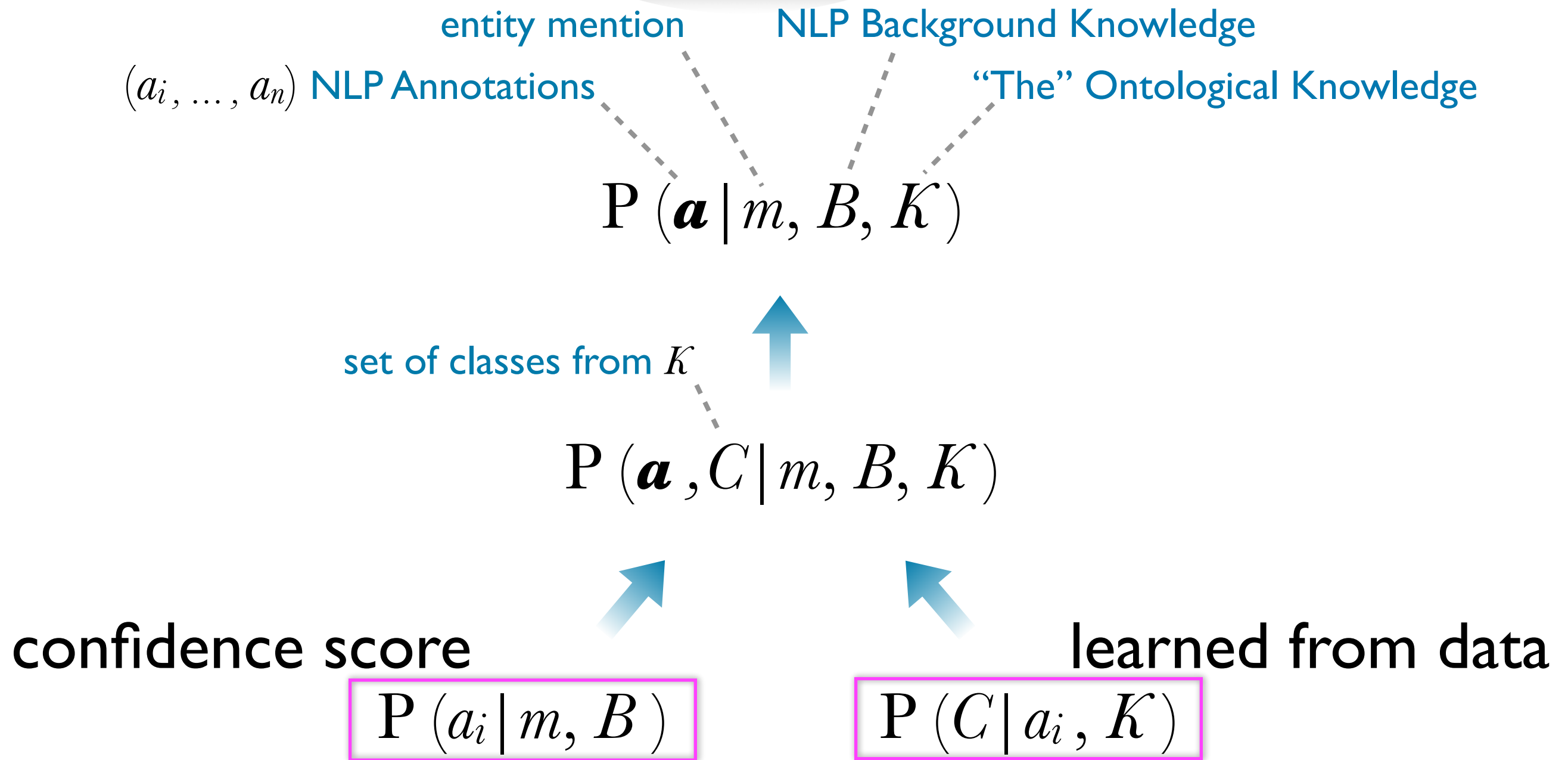
# The JPARK Model



# The JPARK Model



# The JPARK Model



# The JPARK Model

entity mention

NLP Background Knowledge

$(a_i, \dots, a_n)$  NLP Annotations

“The” Ontological Knowledge



$$= \arg \max_{\mathbf{a}} P(\mathbf{a} | m, B, K)$$

set of classes from  $K$

$$P(\mathbf{a}, C | m, B, K)$$

confidence score

$$P(a_i | m, B)$$

learned from data

$$P(C | a_i, K)$$




# **NERC and EL Model**

# Ingredients

- Ontological Knowledge
- Estimating  $P(C | a_{\text{NERC}}, K)$
- Estimating  $P(C | a_{\text{EL}}, K)$

# Ingredients

- Ontological Knowledge  yAGO  
select knowledge
- Estimating  $P(C | a_{\text{NERC}}, K)$
- Estimating  $P(C | a_{\text{EL}}, K)$

# Ingredients


- Ontological Knowledge 

- Estimating  $P(C | a_{\text{NERC}}, K)$

Leverage a **gold standard corpus**  $G$  annotated with NERC types and ontological classes (or EL annotations)

- Estimating  $P(C | a_{\text{EL}}, K)$

# Ingredients

- Ontological Knowledge  **yAGO**  
select knowledge
- Estimating  $P(C | a_{\text{NERC}}, K) \simeq \frac{n_G(C, a_{\text{NERC}})}{\sum_C n_G(C, a_{\text{NERC}})}$  <sup># co-occurrences</sup>  
Leverage a **gold standard corpus**  $G$  annotated with NERC types and ontological classes (or EL annotations)
- Estimating  $P(C | a_{\text{EL}}, K)$

# Ingredients

- Ontological Knowledge 

- Estimating  $P(C | a_{\text{NERC}}, K) \simeq \frac{n_G(C, a_{\text{NERC}})}{\sum_C n_G(C, a_{\text{NERC}})}$  <sup># co-occurrences</sup>

Leverage a **gold standard corpus**  $G$  annotated with NERC types and ontological classes (or EL annotations)

- Estimating  $P(C | a_{\text{EL}}, K)$

Leverage **alignments** between EL Knowledge Base and 

# Ingredients

- Ontological Knowledge 

- Estimating  $P(C | a_{\text{NERC}}, K) \simeq \frac{n_G(C, a_{\text{NERC}})}{\sum_C n_G(C, a_{\text{NERC}})}$  <sup># co-occurrences</sup>

Leverage a **gold standard corpus**  $G$  annotated with NERC types and ontological classes (or EL annotations)

- Estimating  $P(C | a_{\text{EL}}, K) \begin{cases} 1 & \text{entity } a_{\text{EL}} \text{ is instance of } C \\ 0 & \text{otherwise} \end{cases}$

Leverage **alignments** between EL Knowledge Base and 

# Application and Evaluation



# Tools

- **NERC: Stanford CoreNLP** [Finkel et al., 2005]

- **EL: DBpediaSpotlight** [Daiber et al., 2013]

# NERC+EL Datasets

- AIDA CoNLL-YAGO [Hoffart et al., 2011]
- MEANTIME [Minard et al., 2016]
- TAC-KBP [Ji et al., 2011]

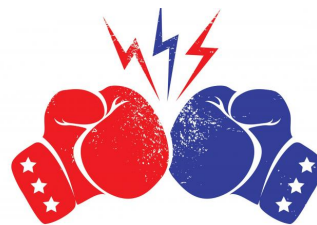
# Research Question

Does the JPARK posteriori joint revision of the annotations from Stanford NER and DBpedia Spotlight, via YAGO, **improve** their NERC and EL performances?

# Research Question

Does the JPARK posteriori joint revision of the annotations from Stanford NER and DBpedia Spotlight, via YAGO, **improve** their NERC and EL performances?

**Stanford CoreNLP**



# Results

	NERC			EL			NERC+EL		
	<i>P</i>	<i>R</i>	<i>F<sub>1</sub></i>	<i>P</i>	<i>R</i>	<i>F<sub>1</sub></i>	<i>P</i>	<i>R</i>	<i>F<sub>1</sub></i>
AIDA									
<i>standard</i>	94.30%	87.50%	90.80%	66.20%	65.20%	65.60%	63.40%	62.50%	63.00%
<i>with JPARK</i>	95.00%	88.10%	91.40%	67.10%	65.40%	66.20%	65.50%	63.70%	64.60%
$\Delta$	<b>0.70%</b>	<b>0.60%</b>	<b>0.60%</b>	<b>0.90%</b>	<b>0.20%</b>	<b>0.60%</b>	<b>2.10%</b>	<b>1.20%</b>	<b>1.60%</b>
MEANTIME									
<i>standard</i>	88.20%	69.50%	77.70%	70.30%	55.60%	62.10%	63.50%	50.20%	56.10%
<i>with JPARK</i>	91.40%	72.00%	80.50%	70.50%	55.70%	62.20%	67.00%	53.00%	59.20%
$\Delta$	<b>3.20%</b>	<b>2.50%</b>	<b>2.80%</b>	0.20%	0.10%	0.10%	<b>3.50%</b>	<b>2.80%</b>	<b>3.10%</b>
TAC-KBP									
<i>standard</i>	91.10%	65.20%	76.00%	40.10%	42.30%	41.20%	36.70%	38.60%	37.60%
<i>with JPARK</i>	92.60%	66.30%	77.20%	41.20%	42.60%	41.90%	38.90%	40.20%	39.50%
$\Delta$	<b>1.50%</b>	<b>1.10%</b>	<b>1.20%</b>	<b>1.10%</b>	0.30%	<b>0.70%</b>	<b>2.20%</b>	<b>1.60%</b>	<b>1.90%</b>

**Bold = statistical significant (approx. rand. test)**

# Results

	NERC			EL			NERC+EL		
	<i>P</i>	<i>R</i>	<i>F<sub>1</sub></i>	<i>P</i>	<i>R</i>	<i>F<sub>1</sub></i>	<i>P</i>	<i>R</i>	<i>F<sub>1</sub></i>
<b>AIDA</b>									
<i>standard</i>	94.30%	87.50%	90.80%	66.20%	65.20%	65.60%	63.40%	62.50%	63.00%
<i>with JPARK</i>	95.00%	88.10%	91.40%	67.10%	65.40%	66.20%	65.50%	63.70%	64.60%
$\Delta$	<b>0.70%</b>	<b>0.60%</b>	<b>0.60%</b>	<b>0.90%</b>	<b>0.20%</b>	<b>0.60%</b>	<b>2.10%</b>	<b>1.20%</b>	<b>1.60%</b>
<b>MEANTIME</b>									
<i>standard</i>	88.20%	69.50%	77.70%	70.30%	55.60%	62.10%	63.50%	50.20%	56.10%
<i>with JPARK</i>	91.40%	72.00%	80.50%	70.50%	55.70%	62.20%	67.00%	53.00%	59.20%
$\Delta$	<b>3.20%</b>	<b>2.50%</b>	<b>2.80%</b>	0.20%	0.10%	0.10%	<b>3.50%</b>	<b>2.80%</b>	<b>3.10%</b>
<b>TAC-KBP</b>									
<i>standard</i>	91.10%	65.20%	76.00%	40.10%	42.30%	41.20%	36.70%	38.60%	37.60%
<i>with JPARK</i>	92.60%	66.30%	77.20%	41.20%	42.60%	41.90%	38.90%	40.20%	39.50%
$\Delta$	<b>1.50%</b>	<b>1.10%</b>	<b>1.20%</b>	<b>1.10%</b>	0.30%	<b>0.70%</b>	<b>2.20%</b>	<b>1.60%</b>	<b>1.90%</b>

**Bold = statistical significant (approx. rand. test)**

# Results

	NERC			EL			NERC+EL		
	<i>P</i>	<i>R</i>	<i>F<sub>1</sub></i>	<i>P</i>	<i>R</i>	<i>F<sub>1</sub></i>	<i>P</i>	<i>R</i>	<i>F<sub>1</sub></i>
<b>AIDA</b>									
<i>standard</i>	94.30%	87.50%	90.80%	66.20%	65.20%	65.60%	63.40%	62.50%	63.00%
<i>with JPARK</i>	95.00%	88.10%	91.40%	67.10%	65.40%	66.20%	65.50%	63.70%	64.60%
$\Delta$	<b>0.70%</b>	<b>0.60%</b>	<b>0.60%</b>	<b>0.90%</b>	<b>0.20%</b>	<b>0.60%</b>	<b>2.10%</b>	<b>1.20%</b>	<b>1.60%</b>
<b>MEANTIME</b>									
<i>standard</i>	88.20%	69.50%	77.70%	70.30%	55.60%	62.10%	63.50%	50.20%	56.10%
<i>with JPARK</i>	91.40%	72.00%	80.50%	70.50%	55.70%	62.20%	67.00%	53.00%	59.20%
$\Delta$	<b>3.20%</b>	<b>2.50%</b>	<b>2.80%</b>	0.20%	0.10%	0.10%	<b>3.50%</b>	<b>2.80%</b>	<b>3.10%</b>
<b>TAC-KBP</b>									
<i>standard</i>	91.10%	65.20%	76.00%	40.10%	42.30%	41.20%	36.70%	38.60%	37.60%
<i>with JPARK</i>	92.60%	66.30%	77.20%	41.20%	42.60%	41.90%	38.90%	40.20%	39.50%
$\Delta$	<b>1.50%</b>	<b>1.10%</b>	<b>1.20%</b>	<b>1.10%</b>	0.30%	<b>0.70%</b>	<b>2.20%</b>	<b>1.60%</b>	<b>1.90%</b>

**Bold = statistical significant (approx. rand. test)**



# Research Question

Does the JPARK posteriori joint revision of the annotations from Stanford NER and DBpedia Spotlight, via YAGO, **improve** their NERC and EL performances?





# Conclusions

- **Novel** probabilistic model, leveraging **ontological knowledge**, for improving NLP entity annotations
- Instantiation of the model for the **NERC** and **EL** tasks
- **Empirical confirmation** (3 datasets) of the capability of the model to improve the quality of the annotations
- Future Work: **extension** to other tasks (e.g., SRL)



[rdfpro.fbk.eu](http://rdfpro.fbk.eu)



# Marco Rospocher



[rospocher@fbk.eu](mailto:rospocher@fbk.eu)  
[dkm.fbk.eu/rospocher](http://dkm.fbk.eu/rospocher)  
[@marcorospocher](https://twitter.com/marcorospocher)

**BPMN Ontology**  
[dkm.fbk.eu/bpmn-ontology](http://dkm.fbk.eu/bpmn-ontology)



Event & Situation Ontology  
[github.com/newsreader/eso](https://github.com/newsreader/eso)



[github.com/dkmfbk/TeXOwl](https://github.com/dkmfbk/TeXOwl)

